The heterogeneity of inter-contact time distributions: its importance for routing in delay tolerant networks

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Abstract Prior work on routing in delay tolerant networks (DTNs) has commonly made the assumption that each pair of nodes shares the same inter-contact time distribution as every other pair. The main argument in this paper is that researchers should also be looking at heterogeneous inter-contact time distributions. We demonstrate the presence of such heterogeneity in the often-used Dartmouth Wi-Fi data set. We also show that DTN routing can benefit from knowing these distributions. We first introduce a new stochastic model focusing on the inter-contact time distributions between all pairs of nodes, which we validate on real connectivity patterns. We then analytically derive the mean delivery time for a bundle of information traversing the network for simple single copy routing schemes. The purpose is to examine the theoretic impact of heterogeneous inter-contact time distributions. Finally, we show that we can exploit this user diversity to improve routing performance.

1 Introduction

In the kind of delay tolerant networks (DTNs) [1] that we consider in this paper, nodes are mobile and have wireless networking capabilities. They are able to communicate with each other only when they are within transmission range. The network suffers from frequent connectivity disruptions, making the topology only intermittently and partially connected. This means that there is a very low probability that an end-to-end path exists between a given pair of nodes at a given time. Such DTNs can be consider in ad hoc networking when connectivity is very low (e.g. in tactical military communications), in transportation systems as in the DieselNet project [2] or in Pocket Switched Networks (PSN) [3] which are formed by devices that people carry everyday (cell phones, PDAs, music players). In all these contexts, end-to-end paths can exist temporarily, or may sometimes never exist, with only partial paths emerging. This paper addresses the extreme case, where only temporal paths exist. We call such networks *temporal DTNs*, or *t-DTNs*. When a node in a t-DTN receives a “bundle” of information from a neighboring node, it keeps it until it meets another node which provides an opportunity to relay the bundle. The bundle is transfered from one node to another instantly and this transfer is atomic.

Prior work on routing in t-DTNs has commonly made the assumption that each pair of nodes shares the same inter-contact time distribution as every other pair. The main argument in this paper is that researchers should also be looking at cases in which inter-contact time distributions are heterogeneous. Chaintreau et al. [3] posit that there might be heterogeneity, but we show it and characterize it. We also show how exponential distributions can be composed to yield the heavy-tailed distributions that Chaintreau et al. observed. As we shall see, the heterogeneity that we highlight allows us to usefully extend the work of Spyropoulos et al. [4,5], which analyzes numerous routing schemes for t-DTNs, but that uses mobility models that yield homogeneous distributions.

We show, on the well known Dartmouth Wi-Fi data set [6], that despite the existence of a heavy-tailed distribution when inter-contact times are considered in the aggregate, a large portion of the node pairs present inter-contact time distributions that can be well fitted by an exponential distribution. We found these distributions to be heterogeneous, with a wide variation in exponents.

We also provide the first formal analysis of the impact of heterogeneous exponential inter-contact time distributions on simple single-copy routing schemes. We show that routing strategies can benefit, in terms of delay, from this heterogeneity, and in particular from knowing these distributions. A node can choose among possible relay nodes based upon their expectations for meeting other relays or the destination.

2 Inter-contact time model

This section presents the model we use to analytically derive the delay expectations for the routing protocols we study later in this paper.

2.1 Exponential t-DTNs

We consider a network composed of n nodes. Let's first look at the inter-contact time between two individual nodes (i,j): $t_{ij}^1 < t_{ij}^2 < t_{ij}^3 < \dots$ are the successive instants at which a contact between i and j occurs.

$$\Delta t_{ij}^k = t_{ij}^{k+1} - t_{ij}^k \tag{1}$$

is the inter-contact time between the k^{th} and $(k+1)^{th}$ contact instants.

We assume that the Δt_{ij}^k are samples from independent and identically distributed random variables that follow an exponential law with parameter λ_{ij}, which we note $\tau_{ij} = \text{exponential}(\lambda_{ij})$. The mean inter-contact time between i and j is thus given by $E[\tau_{ij}] = 1/\lambda_{ij}$.

In the overall network, all n nodes are supposed to behave independently, so that the $n(n-1)/2$ pairwise inter-contact times τ_{ij} are independent exponential processes with different parameters. The τ_{ij} family of processes is symmetric and $\forall i, \tau_{ii} = 0$. The exponential t-DTN is thus entirely and uniquely characterized by the $n(n-1)/2$ strictly positive real parameters λ_{ij}.

2.2 Assumptions

The model focuses on the temporal dynamics of node connectivity in a DTN. In this way it provides a common framework to analyse different DTNs. In particular it applies very well to social networks for which the position of nodes at a given time is not of primary importance. We believe this abstraction helps focus on the inherent characteristics of intermittent connectivity in DTNs.

Characterizing inter-contact time behavior helps abstract away from the spatial information that is essential in the analysis of mobile ad hoc networks. There is no reference to geographic, localisation or any other such spatial information. There is also no reference to air interface parameters, quality of or contention on the links, etc. Node mobility is not explicitly modelled: only its aggregated impact on the inter-contact time is taken into account.

The model makes a stationarity hypothesis with respect to node inter-contact time distributions. In other words, nodes behaviors are assumed to change on a slower scale than bundle exchanges. We also suppose that nodes have infinite capacity in bandwidth and storage.

Another key hypothesis is that contacts (and thus bundle transfers) are assumed to be instantaneous. In the model, pairwise contacts do not overlap: in contrast to the mobile ad hoc network cases, no partial routes (involving more than two nodes) exist at any given time.

In this respect, the results with the proposed model are upper bounds, but, as we will see, still provide valuable information and insight on how to route bundles in DTNs. We leave refinements of the model for future work.

3 Fitting the model

In the t-DTN model just elaborated, we assume that the inter-contact time distribution for each pair of nodes is exponential. The main reason is that it will allow us to go beyond asymptotic results and provide explicit formulas for the bundle delivery time, and other parameters, of different routing protocols. In this section we look at real data to evaluate how reasonable this hypothesis might be.

3.1 Experimental data set

To validate the hypothesis, we use real data from the Wi-Fi access network of Dartmouth College [6]. These data track users' sessions in the wireless network by showing the time at which a node associates or dissociates from an access point. We use the subset of data pre-processed by Song et al. for their prior work [7] on mobility prediction.

As we describe in prior work [8], we must select from the data, and make some assumptions, in order to constitute a useful DTN data set. We take the subset of users who are present in the network every day between January 26$^{\text{th}}$ 2004 and March 11$^{\text{th}}$ 2004, a class period during which we expect nodes' activity to be fairly stationary. This data set contains 834 users, or nodes. Then, we assume that two nodes are in contact if they are present at the same time at the same access point (AP). Finally, we filter these data to remove the well known *ping-pong* effect. Indeed, wireless nodes, even non-mobile, can oscillate at a high frequency between two APs. To counter this, we filter all the inter-contact times below 1,800 seconds. Note that defining better filtering methods, albeit challenging, would be of interest for the community. As this is not the purpose of this work, We choose here the threshold that Yoon et al. [9] used for the same purpose. We use this new data set for the remainder of this paper.

The Wi-Fi scenario may be not a perfect fit for interactions between nodes in t-DTNs. Indeed, in opposition to always-on devices carried by humans, Wi-Fi nodes are typically turned off, transported, and then turned on again, thus missing potential contacts en route. However, the size, quality, and public availability of the data set make it nonetheless one of the best resources for this kind of study. Jones et al. [10] and Chaintreau et al. [3] recently used these traces in a similar way.

3.2 Exponential inter-contacts

Fig. 1 shows the distribution of $E[\tau_{ij}]$, the expected inter-contact time for the pair of nodes (i, j). This plot has been computed over all the $28,490$ source-destination pairs that experienced an average inter-contact time lower than one week within the two months period that we considered in Dartmouth data. We can see that the distributions are heterogeneous with expectations varying over three orders of magnitude. The average $E[\tau]$ is 11.6 hours with a variance of 7.1 hours.

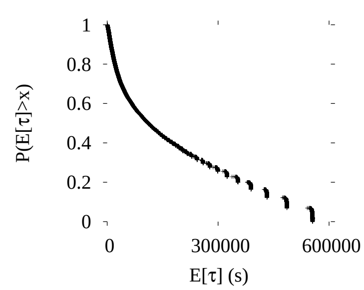


Fig. 1 Distribution of $E[\tau]$.

Then, we test for whether the inter-contact process between any two nodes can be modelled by an exponential process with a parameter $\lambda = 1/E[\tau]$. We use the Cramer-Smirnov-Von-Mises [11] hypothesis test. For each pair (i, j), we compare the cumulative distribution I_N^{ij} for the N inter-contacts observed and the hypothesis function whose cumulative distribution is $F_{ij}(x) = 1 - \exp(-\lambda_{ij}x)$. We also compare I_N^{ij} with that of a power law distribution. Note that we only perform the

computation for pairs that show a sufficient level of connectivity by having a mean inter-contact time lower than one week and that have more than 20 contacts. We identify 8,402 pairs to be exponentially distributed and 28 with a power law which makes respectively, 62.3% and 0.2% of the $13,482$ pairs that we retain for the test.

From these observations, it seems clearly more reasonable, in this data set, to model pairwise inter-contact time distributions as exponential rather than power law since a large number of pairs have shown inter-contact times exponentially distributed. Despite that few are power law distributed, we conjecture that the rest of pairs might follow distributions that are a mix of exponential and power law distributions. As we have examined only one data set, albeit an often-used one, we cannot draw many conclusions about what will be revealed elsewhere. It is reasonable to expect that other mobility traces in campus environments will show similar characteristics. However, it is surprising that a memoryless process seems to be at work in such a high proportion of node pairs in an environment in which one would expect some temporal correlations. We hope this will be a spur to study these distributions in other data sets. Traces from the Haggle project [3] or the ones of the Reality Mining project [12] might be considered. We let this study for future work.

3.3 Power laws

Chaintreau et al. [3] observed that aggregated inter-contact times follow power laws in a number of DTN traces (also including one based on the Dartmouth data). Fig. 2 shows that, for our data set, the cumulative distribution of aggregated inter-contact times also follows a power law of the form $f(x) = cx^{\delta}$, with exponent $\delta = -0.16$ and scale parameter $c = 3.45$.

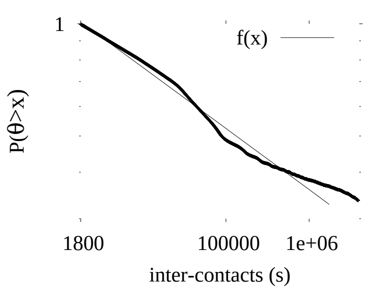


Fig. 2 Distribution of inter-contacts in logarithmic scale.

Let's now consider what happens for pure exponential t-DTNs where all pairwise inter-contact time distributions are exponentially distributed. Under which conditions do the aggregated inter-contact time distributions follow a power law, or is the pairwise exponential assumption too strong to yield a power law in the aggregate?

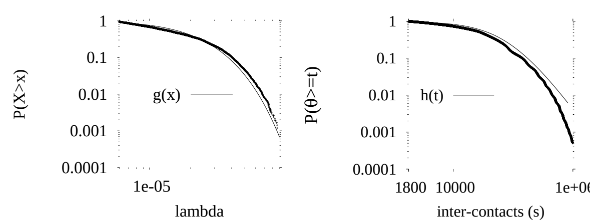
Let Θ be the aggregated inter-contact time for all pairs of nodes, and let $p(\lambda)$ be the probability distribution of the λ parameters:

$$P(\Theta > t) = \int_{\lambda=0}^{\infty} e^{-\lambda t} p(\lambda) d\lambda \quad (2)$$

What eqn. 2 says is that, for exponential t-DTNs, the aggregated inter-contact time distribution is fully characterized by the distributions of the λ parameters, and thus of the $E[\tau_{ij}]$ matrix. More precisely, the tail cumulative distribution of the aggregated inter-contact times is given by the Laplace transform of the distribution p of the λ parameters.

A Pareto law of the form $(\frac{b}{t+b})^{\alpha}$, $t \geq 0$, with shape parameter $\alpha > 0$ and scale parameter $b > 0$, is observed if and only if the λ follow a gamma distribution $p(\lambda) = \frac{\lambda^{\alpha-1} b^{\alpha} e^{-b\lambda}}{\Gamma(\alpha)}$, $\lambda \geq 0$.

To verify this on the data set we proceed in the following way: we estimate parameters α and b from the cumulative distribution of the λ parameters for pairs that were shown to follow an exponential behavior (the ones that pass the Cramer hypothesis test). We find $b = 113,766.9$ and $\alpha = 2.26$. Fig. 3(a) shows the estimated cumulative gamma distribution $g(x)$ with the experimental lambda cumulative distribution for all pairs that have shown to be exponential. Then, we plot in Fig. 3(b) the corresponding power-law $h(t)$ with cumulative distribution of aggregated inter-contact times. As one can see, the two experimental curves fit the theoretical curves.



(a) λ_{ij} (b) Inter contacts

Fig. 3 Distributions with exponential pairs.

What this result shows is that when one considers an exponential t-DTN, we can regain the power law behavior for the aggregated inter-contacts when the distribution of the parameters is a gamma, which is the case in the data we used when considering the subset of pairs that have inter-contact times exponentially distributed.

4 Single copy routing strategies

Having defined a stochastic model that is realistic for the data set under study, we now examine different simple single copy routing strategies. We derive analytical formulas that we will use to study the impact of heterogeneous λ_{ij} parameters on routing.

In all routing strategies, we consider that nodes know all pairwise mean inter-contact times for all nodes in the network, i.e., each node knows the λ_{ij} matrix. This knowledge could be diffused through an epidemic type of routing, or learned by each node from past contacts.

4.1 Wait scheme

Under the Wait routing strategy, the source node s waits until it meets d, the destination, to deliver the bundle in one hop.

If the bundle is injected at time t, its delivery time is equal to R_{sd}^{t}, the remaining inter-contact time before the next contact between nodes s and d. The memoryless nature of exponentials implies that R_{sd}^{t} also follows an exponential distribution with the same parameter. The mean expected delivery is thus given by:

$$E[D_{sd}^{w}] = 1/\lambda_{sd} \quad (3)$$

This straightforward result gives an upper bound on the delivery time that a routing strategy should meet, since the Wait strategy is the most rudimentary one hop single copy scheme.

4.2 MED

The Minimum Expected Delay (MED) routing strategy was first introduced by Jain et al. [13]. This strategy, similar to source routing, defines which path the bundle will follow from s to d, that is, the ordered list of intermediate relay nodes it will have to go through. The list is chosen to provide minimum expected end-to-end delay.

If a path is given by the following ordered list of nodes $r_0 = s < r_1 < r_2 < r_3 < ... < r_{n-1} < r_n = d$, and relaying occurs at time instants $t_1 < t_2 < ... < t_n$, the total delivery time along path $(s, r_1, r_2, ..., r_{n-1}, d)$ is given by the remaining inter-contact time after each relaying instant, that is:

$$D_{s,r_1,r_2,...,r_{n-1},d}^{med} = R_{sr_1}^{t_1} + R_{r_1r_2}^{t_2} + ... + R_{r_{n-1}d}^{t_n} \quad (4)$$

Using the fact that $E[R_{r_ir_j}] = 1/\lambda_{ij}$, the expected delivery time along the path is thus given by:

$$E[D_{s,r_1,r_2,...,r_{n-1},d}^{med}] = 1/\lambda_{sr_1} + 1/\lambda_{r_1r_2} + ...1/\lambda_{r_{n-1}d} \quad (5)$$

Finding the optimal path thus amounts to finding a lowest-weight path between nodes s and d in a graph in which the weight on each link (i, j) is defined as $1/\lambda_{ij}$. Dijkstra's algorithm can be used.

4.3 Spray and Wait routing

The Spray and Wait strategy was first introduced by Grossglauser and Tse [14], and is designed to take advantage of opportunistic contacts. It consists of two steps. First the source node uses the first nodes encountered as relays to the destination. This is the "spraying" step. A relay node then uses the "wait" strategy to relay the bundle, i.e. it waits until it meets the destination to deliver the bundle. Here, we study the case where only one relay is used, which we designate 1-SW.

Let us first consider the spraying step. The bundle is injected at source s at time instant t. The first node r it encounters may be any of the $n-1$ other nodes $d, r_1, r_2, ..., r_{n-2}$ and the time X it takes to meet this first node is the infinum of the inter-contact times with all other nodes:

$$X = inf(R_{sd}^{t}, R_{sr_1}^{t}, ..., R_{sr_{n-2}}^{t}) \quad (6)$$

Since all $R_{sr_i}^{t}$ are independent exponentials with parameters λ_{sr_i}, we have (see [15, p.328]):

- The random index r of the first node encountered is independent of the first encounter time X
- X is exponentially distributed, with parameter: $\Lambda_s = \lambda_{sd} + \sum_{i=1}^{n-2}(\lambda_{sr_i})$
- $\Pr(First\ node\ encountered\ is\ r) = \frac{\lambda_{sr}}{\Lambda_s}$

This means that we can represent the spraying step as independently identifying the encountered node (with probability $\frac{\lambda_{sr}}{\Lambda_s}$) and adding an exponential waiting time with parameter Λ_s.

Two cases may arise: either the first node encountered r equals d, and s delivers the bundle, or $r \neq d$ and node r waits to meet node d to deliver the bundle.

The delivery time Z_d, when node d is encountered first is thus given by:

$$E[Z_d] = \frac{1}{\Lambda_s} \quad (7)$$

The delivery time Z_r along path r, i.e., conditioned on using node r as a relay, is thus the sum of the first encounter time X and the remaining delivery time between nodes r and d, and thus:

$$E[Z_r] = \frac{1}{\Lambda_s} + \frac{1}{\lambda_{rd}} \quad (8)$$

The total delivery time Z is computed by conditioning on all possible first encountered nodes $d, r_1, r_2, ..., r_{n-2}$, events whose probabilities are given by $\frac{\lambda_{sr}}{\Lambda_s}$:

$$E[Z] = \frac{\lambda_{sd}}{\Lambda_s} E[Z_d] + \sum_{i=1}^{n-2} \left(\frac{\lambda_{sr_i}}{\Lambda_s} E[Z_{r_i}]\right) \quad (9)$$

After simplification, we can state that: in a network composed of n nodes, 1-SW delivers a bundle from source s to destination d with mean delivery time given by:

$$E[D_{sd}^{1-sw}] = \frac{(1 + \sum_{r \neq s, r \neq d} \frac{\lambda_{sr}}{\lambda_{rd}})}{\sum_{r \neq s} \lambda_{sr}} \quad (10)$$

5 Comparing routing protocols

This section looks at routing performance of the protocols we considered in the presence of heterogeneity in inter-contact time distributions.

In this context, we present 1-SW*, a variation of 1-SW. Instead of spraying its bundle to the first node that it encounters, the source node s sprays only to nodes in a subset R. We call this a 1-SW^R scheme. We define 1-SW* to be a 1-SW^R scheme which uses a subset R that minimizes $E[D_{sd}^{1-sw^R}]$. Following the same line of reasoning as in Sec. 4.3, and defining $1/\lambda_{dd} = 0$, one finds that the expected delivery time is given by:

$$E[D_{sd}^{1-sw^R}] = \frac{(1 + \sum_{r \in R} \frac{\lambda_{sr}}{\lambda_{rd}})}{\sum_{r \in R} \lambda_{sr}} \quad (11)$$

We performed simulations using Dartmouth traces (see Sec. 3) to study how the algorithms behave in the case of heterogeneous connectivity. We simulate the following protocols: Wait

and 1-SW which are naive schemes, and, 1-SW* and MED that are designed to take advantage of heterogeneity. We slightly modified 1-SW, to better compare it with 1-SW*: a node i is a potential relay only if $\lambda_{id} > 0$, i.e., if it has a chance of meeting the destination. In MED, we authorized intermediary relays to directly transfer bundles to the destination whenever met.

We choose at random 100 different source destination pairs (s,d) and replay the contacts between the 835 nodes present in the data to see how for each pair a bundle, generated at the beginning of the two months period, is delivered.

λ values used for route selection in 1-SW* and MED, and to determine theoretical delays of 1-SW, 1-SW* and MED have been computed over the data filtered due to the ping-pong effect (see Sec.3). However, the contacts replayed in simulations were that in the original traces as it does not impact the results and because filtering was only of interest for modelling.

	delivery ratio (%)	**A delay** (days)	**M delay** (days)	**th. delay** (days)	**hop count** (hops)
Wait	11.2 ± 0.9	19.8 ± 3.7	16.3 ± 10.3	41.3 ± 0.5	1.0 ± 0.0
1-SW	87.3 ± 3.0	23.0 ± 0.9	22.7 ± 2.7	15.3 ± 0.9	2.0 ± 0.1
1-SW*	86.9 ± 2.0	18.8 ± 0.4	15.4 ± 0.9	13.0 ± 1.1	2.0 ± 0.1
MED	87.9 ± 2.2	20.9 ± 0.7	18.0 ± 1.1	1.3 ± 0.2	7.2 ± 0.2

Table 1 Simulation results with Dartmouth data.

Table 1 presents the simulation results averaged over 5 runs with the 90% confidence levels that are obtained using the Student t distribution. It presents, for each of the protocols, the average delivery ratio, the average delay ("A delay") and the median delay ("M delay") computed over the delivered bundles, the average theoretical delay over all the bundles generated (infinite delay is assumed to be the length of the simulated period, i.e. 45 days), and the average hop count, also obtained on delivered bundles.

The major result in Table 1 is that schemes that make use of heterogeneity of inter-contact times (1-SW* and MED) perform better, either in delivery ratio or delay, than the ones that do not exploit it (Wait and 1-SW). Wait only delivers 11.2% of bundles because most of the source, destination pairs selected at random satisfy $\lambda_{sd} = 0$ (e.g. they never met). 1-SW, 1-SW* and MED achieve almost the same delivery ratios with respectively 87.3%, 86.9% and 87.9%. About 13% of the bundles were thus not delivered. In terms of delay, among these last three protocols, 1-SW plots the highest with a mean of 23.0 and a median of 22.7 in days, 1-SW* the lowest with a mean of 18.8 and a median of 15.4. MED appears to be in the mid-range with a mean of 20.9 and a median of 18.0 in days.

The difference between the modified 1-SW and 1-SW* gives a further insight on the type of heterogeneity that should be considered. The modified 1-SW is a one hop strategy that uses only true relays to the destination: relay nodes in 1-SW must meet both the source and the destination. The scheme is not completely ignorant of heterogeneity, as it exploits binary connectivity information, the fact that not all nodes meet one another. 1-SW* goes beyond that and differentiates between neighboring nodes based on the quantitative expected inter-contact time. The fact that 1-SW* ourperforms the modified 1-SW thus indicates that routing actually benefits from the quantitative inter-contact time heterogeneity, and not just from node connectivity.

Table 1 shows a descrepancy between the theoretical and the experimental delays. This can be first explained by the presence of node pairs that do not have an exponential behavior. This is particularly true for 1-SW*. In this case the computation of expected delays on mean inter-contact times misses possible inter-dependencies of node contacts.

Simulation artifacts also come into play. The routing simulation is carried out on a limited time scale. The λ values are computed over the entire data set in a prior pass, so a relay node may meet the destination for the last time before having met the source for the first time. This pre-computation being not realistic, we could have used on-line predictive or learning methods. However, as they are challenging to define, we let this study for future work and intend here to provide early validation results to motivate research in the domain. The fact that 1-SW* delivers slightly less bundles than 1-SW is clearly due to this artefact. Indeed, because in 1-SW, the source transfers more rapidly the bundle to a relay, we have a lower probability to contacts between that relay and the destination. Also, MED suffers from the same simulation artefact, it would have delivered 100% of bundles otherwise.

Through these simulations, we validate the natural feeling that we should take into account the heterogeneity of inter-contact time distributions in the design of routing solutions for t-DTNs. Furthermore, because 1-SW*, which is only a two-hop protocol, achieves better performance than MED by delivering bundles with lower delays and a lower impact on network resources (MED delivers bundles in 7.2 hops in average while 1-SW* uses only 2), we expect promising future work inspired from 1-SW* to be done. The opportunistic nature of 1-SW* is the main reason of this superiority over MED, in which bundles follow a strict sequence of relays, in a network which is not a perfect exponential t-DTN.

6 Conclusion

We have first shown that, in a widely-used t-DTN data set, distributions of inter-contact times are heterogeneous. As a consequence, one has to take it into account while modeling. Second, we have validated the insight that considering heterogeneity in routing improves performance. We presented a simple routing strategy, 1-SW*, adapted from the Spray and Wait scheme, which is capable of using only a subset of relays to improve routing performance, measured in term of average delay.

Clearly, our work, based as it is upon one data set, will benefit from validation against others as mentioned in Sec. 3. Work also needs to be done to examine why a memoryless model fits so many node pairs in an environment in which one would expect to find more temporal correlations. Finally, formal studies and validations should be conducted with more elaborate schemes, in terms of number of copies distributed or in terms of the number of hops traversed.

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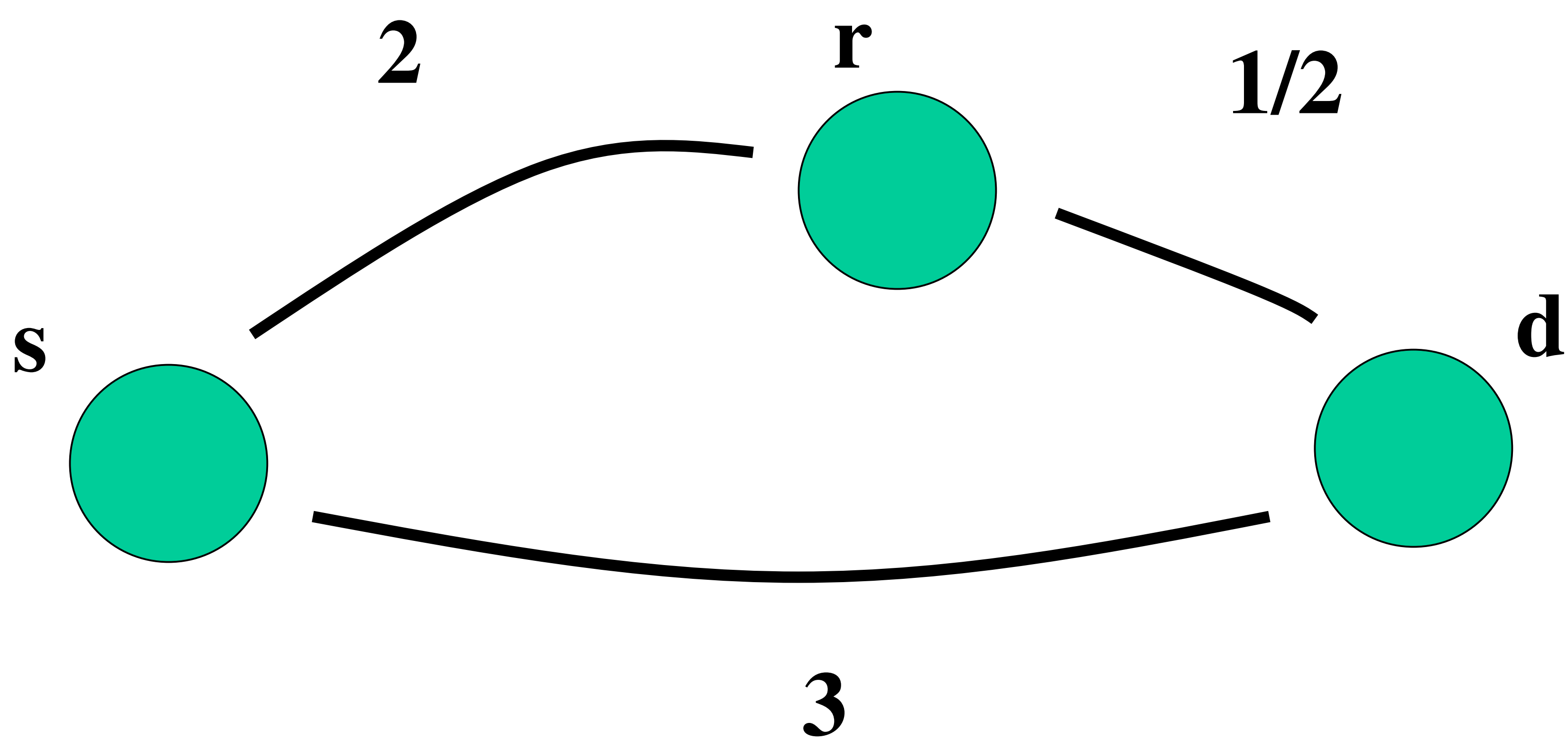
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